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Plant leaf detection through machine learning based image classification approach

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ABSTRACT

Since maize is a staple diet for people, especially vegetarians and vegans, maize leaf disease has a significant influence here on the food industry including maize crop productivity. Therefore, it should be understood that maize quality must be optimal; yet, to do so, maize must be safeguarded from several illnesses. As a result, there is a great demand for such an automated system that can identify the condition early on and take the appropriate action. Early disease identification is crucial, but it also poses a major obstacle. As a result, in this research project, we adopt the fundamental k-nearest neighbor (KNN) model and concentrate on building and developing the enhanced k-nearest neighbor (EKNN) model. EKNN aids in identifying several classes of disease. To gather discriminative, boundary, pattern, and structurally linked information, additional high-quality fine and coarse features are generated. This information is then used in the classification process. The classification algorithm offers high-quality gradient-based features. Additionally, the proposed model is assessed using the Plant-Village dataset, and a comparison with many standard classification models using various metrics is also done.

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1. INTRODUCTION

Recent advances in technology and the use of algorithms for machine learning have changed several industries, including electronic media, medicine, defense, engineering, as well as agriculture [1]. Agriculture has had the most recent and significant growth among these fields [2], and it has benefited greatly from these clever technological advancements. The implementation of smart agricultural practices can play a pivotal role in boosting a country's economy, particularly when agriculture serves as its primary source of revenue. Moreover, certain crops hold substantial influence on the nation's economic well-being, with many of these crops being cultivated domestically and even exported. Corn stands out as one of these pivotal crops within the agricultural sector [3]. Maize, a vital traditional crop, serves as a staple for both human and animal consumption, while also serving as a fundamental raw material for various industries [4]. It is important to note that both crop yield and maize production significantly impact the quality of maize kernels [5]. Therefore, there is a pressing need for a rapid and efficient method to evaluate the nutritional value of maize kernels [6]. However, the presence of several leaf diseases affecting maize crops can lead to a substantial reduction in yield [7] and crop quality. Furthermore, these plant leaf diseases can significantly diminish the

output rates of maize crops [8]. Hence, precise identification of leaf diseases is of paramount importance to sustain production rates and crop yields.

According to [7], an support vector machine (SVM) classifier-based classification of leaf illnesses is used to identify maize diseases. Furthermore, given is a thorough study on the segmentation of leaf diseases. In [8], a convolutional neural network (CNN) architecture is harnessed to detect maize leaf diseases, marking a significant stride in the automation and digitization of agriculture. The CNN architecture greatly enhances the precision of classifying these leaf diseases. Meanwhile, in [9], an alternative machine learning approach is presented for the identification of crop leaf diseases. This approach leverages handcrafted features such as local ternary patterns (LTP), segmented fractal texture analysis, and histogram-oriented gradient (HOG) to provide detailed insights. Furthermore, [10] introduces a method involving feature augmentation and the application of a robust AlexNet approach for maize leaf disease identification. This approach incorporates the resilient AlexNet technique to devise a modified neural network (NN) architecture. Nevertheless, it's important to note that the full potential of plant leaf disease identification methods has not yet been fully realized for practical, real-world applications. Several challenges remain, including the need for accurate disease diagnosis, consideration of various factors influencing crop production and maize quality, and the development of efficient feature extraction techniques for disease type recognition [11].

In this study, crop leaf diseases precisely detected using an enhanced k nearest neighbour (EKNN) classifier. Using the suggested EKNN model, the identification of such leaf disease process is divided into four stages. In addition, the first stage outlines the pre-processing step that removes noise from leaf picture data. Phase 2 also covers how leaf lesions are segmented to determine lesion boundaries and pattern-related data. The proposed technique for feature extraction extracts the structure-related information from maize leaf photos and then discussed in phase 3. Lastly, using the proposed EKNN framework, leaf classification carried out on the features collected for the identification of leaf diseases. The way this research presented is as follows. The mathematical approach of the modified k-nearest neighbour (KNN) algorithm for the classification of maize leaves described in Section 2. The experimental findings discussed in section 3 along with a comparison to conventional leaf categorization methods, and the article concluded in section 4.

2. MODELLING OF THE PROPOSED ENHANCED KNN CLASSIFIER

Leaves are enough to show the health status of corn plants [12]. Brownish leaves or yellowish leaves along with decaying areas and patches can be observed on those plants, which are suffering from any type of disease. We want to extract this information from the image data [13]. Low-dimensional features thought to be discriminative throughout the feature extraction process [14] and resilient to changes in the data. To extract color information, red, green, blue (RGB) features are frequently used in image processing as well as pattern identification. For object identification in photos with significant color fluctuation, RGB is strongly advised [15]. Consider the RGB color as a combination of various hues that produced by combining red, green, and blue lights of various colors. The RGB values were in the range of 1 to 255. In this task, we will normalize those colors from 0 to 1. The various diseases on maize leaves depicted in Figure 1.

Figure 1. Corn leaf disease types

In a recent development, a digital image processing method has been employed for the identification of leaf diseases, with a significant focus on the role of structure in pattern recognition [16]. Structure-related information, in this context, plays a crucial role in extracting essential features such as shape, object patterns, and boundaries. To achieve comprehensive leaf disease identification, structure-related information is categorized into two distinct groups. The first category furnishes fine-grained details, while the second

category conveys information about coarser features [17]. For visual representation, please refer to Figure 2, which illustrates the proposed model's architectural design.

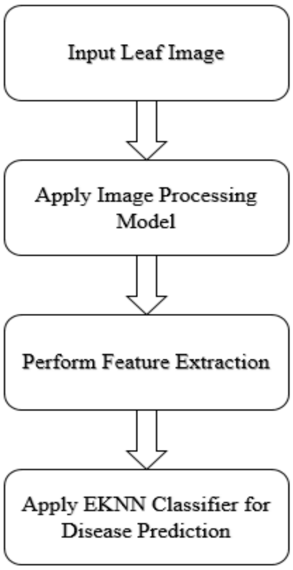

Figure 2. Proposed model architecture

The feature extraction procedure separates the image into a massive number of total feature vectors, where each of which is affected by local geometric distortions and changes in lighting but not by translation, scaling, or rotation of the image [18]. These traits are reminiscent of neurons within the primary visual cortex [19], which are in charge of basic forms, motions for objects, and color identification in primates. This method searches for candidates among related features based on feature vector Euclidian distance. The excellent characteristics are regarded as useful (1).

Let us look at the central (pixel) region of an image M. Fine-the feature could be expressed as (1),

$$fine\_feat_{U,V} = \sum_{u=0}^{U-1} 2^u\, j(S_{t,u} - S_o) \quad (1)$$

The area of a pixel (AoP) value in greyscale for the central and uth neighboring pixels on a circle with radius t is shown in the (1) s_O and $s_{t,}$ Moreover, the entire set of nearby pixels is supplied as U using (2).

$$j(s) = \begin{cases} 1, & s \geq 0 \\ 0, & s < 0 \end{cases} \quad (2)$$

These additional rotational constant fine features are provided by (3).

$$fine\_feat_{t,U}^{V} = \begin{cases} \sum_{u=0}^{U-1} j(S_u - S_o), & E(fine\_feat_{T,U}) \leq 2 \\ U+1, & otherwise \end{cases} \quad (3)$$

The produced fine features in the example above are uniform with $E \leq 2$, and V represents a rotating constant form of $fine\_feat$. In this case, the uniformity evaluator D is defined by (4),

$$E(fine\_feat_{T,U}) = \sum_{t=0}^{T-1} |j(S_u - S_o) - j(S_{U-1} - S_o)| + |j(S_{U-1} - S_o) - j(S_0 - S_o) \quad (4)$$

Additionally, a given equation is used to construct the sign and magnitude components of a particular filter response, and a multi-scale histogram for the same is displayed (5).

$$\begin{aligned} C_u &= |S_{t,u} - S_o| \\ j_{t,u} &= j(S_{t,u} - S_o) \end{aligned} \quad (5)$$

However, the aforementioned elements are encoded to produce a multi-scale histogram that can be represented using (6).

$$coarse\_feat_{T,U} = \sum_{u=0}^{U-1} 2^u . j(C_u - O) \tag{6}$$

In (6), the average value of an input image b_t is conveyed using the letter n, as well as further central AoP was accomplished and encoded using (7), where nJ denotes the value of the central pixels.

$$coarse\_feat_{T,U} = j(S_o - O_k) \tag{7}$$

Furthermore, a confined intensity directional order relation (DOR) is employed to define the intensity correlation among adjacent pixels based on gradient features. This confined Intensity-DOR method utilizes constrained ordinal data to determine the intensity relationships between neighboring pixels surrounding each central art of pixels (AoP). Additionally, an encoding approach based on direction sets (DS) is utilized to distinguish neighboring pixels from the multiset pixels, while also preserving rotational invariance.

After that, encoding is done set-by-set, and it's crucial to determine the dominant direction by altering each pixel's greyscale value from [20] to the supplied average greyscale of the provided shaped portions of the given image. Given picture *N* and the center AoP *y*, the average greyscale is provided by (8).

$$\bar{S}_o = \phi(S_{o,w}) \tag{8}$$

$$\bar{S}_{t,u} = \phi\left(S_{t,u,w}\right) \tag{9}$$

In (9), arbitrarily formed patches with nearby pixelsu^{th} and the size of $w\times w$ can be shown surrounding $S_{O,}$ the AoP with the designation z. Moreover, (·) denotes an average greyscale of both the arbitrary; as a result, this model enhances noise robustness and provides an expanded framework for the leaf illness. Subsequently, adjacent pixels are rotated so they point in the precise dominant direction, which helps generate the rotational constant. Furthermore, the dominant direction was taken into account as a neighboring pixel index in which the difference with AoP is of greater value (10).

$$C = arg \underset{v\in\{0,1.....,V-1\}}{max} \left|\bar{t}_{u,v} - \bar{t}_o\right| \tag{10}$$

The model presented in (10), predicts the class label of the histogram and selects the class with the highest sum of neighboring pixels from among all available classes. In addition, the equation mentioned in the context employs an evaluation coefficient to identify neighboring pixels and incorporates an additional feature set through the utilization of class labels. Furthermore, effective classification is attained by employing multiple class labels to detect leaf diseases in maize leaves.

3. RESULTS AND DISCUSSION

In this area of the study, we assess the suggested technique while taking a variety of parameters into account. Also, the suggested model is contrasted with several existing methodologies. For the comparison analysis, other parameters such as classification accuracy, precision, as well as the area under the curve (AUC) are taken into account [21]. The four unique processes of maize leaf identification are generally followed; the first step is pre-processing, which comprises noise reduction and expedited processing [22]. The second phase is the segmentation procedure, which is used in prior studies to identify the illness area utilizing a visible leaf lesion and precise boundaries. To obtain high quality in the third step, fine and coarse characteristics are extracted.

The proposed methodology for evaluating leaf disease is trained using a sufficient number of image sets, and the leaf disease is taken from the plant village dataset [23]. The dataset for the plant village is divided into four distinct disease categories: healthy classes along with cercospora-leafspot grey, northern leaf blight, as well as common rust [24]. Every class has several leaf diseases that as shown in Table 1 in addition to having photos of 256×256-pixel resolutions. The entire project is simulated using matrix laboratory (MATLAB). Additionally, the suggested model produces high-quality features, and the retrieved features are then subjected to a classification method. The proposed models locate the disease within leaves and identify the specific type of disease to which it belongs. In Table 1, the letters healthy leaves (HL), leaves spot gray (LSG), north leaf blight (NLB), and common leaf rust (CLR).

Table 1 Dataset details

Class	Total Images
HL	1162
LSG	513
NLB	985
CLR	1160
Total Images	3820

3.1. Performance metrics

Here, we assess the model in light of various deep learning measures, including accuracy, specificity, sensitivity as well as AUC. The various metrics are shown in Table 2. Where EKNN sees enormous values for accuracy, specificity, and sensitivity along with AUC of values 99.86, 99.88, 99.60, and 99.75, respectively. The performance metrics are determined by the following formula.

– True positives (TP) are the count of cases that are diagnosed as illnesses.
– The count of instances erroneously identified as having a disease is referred to as the number of false positives (FP).
– A true negative (TN) is the count of instances that were appropriately identified as healthy.
– The quantity of cases that are incorrectly classified as healthy is referred to as an false negative (FN).

Table 2. Performance metric for EKNN

Performance Metrics	Value
Accuracy	99.86
Sensitivity	99.6
Specificity	99.88
AUC	99.75

3.1.1. Accuracy

The ability of a test to accurately differentiate between cases of disease and healthy individuals determines its accuracy. To measure a test's accuracy, we need to find the proportion of TP and TN cases in all examined cases [25]. This can be mathematically stated as (11).

$$Accuracy = TP + TNTP + TN + FP + FN \quad (11)$$

3.1.2. Sensitivity

The capability of a test to accurately identify disease instances is referred to as its sensitivity. To estimate it, figure out the percentage of true positives for cases of leaf disease. This can be mathematically stated as (12).

$$Sensitivity = TPTP + FN \quad (12)$$

3.1.3. Specificity

The ability of a test to accurately identify healthy cases is referred to as its specificity. To estimate it, find the percentage of genuine negatives in healthy circumstances. This can be mathematically stated as (13).

$$Specificity = TNTN + FP \quad (13)$$

Two cutting-edge techniques, namely dilated multiscale-robust (DMS) AlexNet and AlexNet, are compared. The model's name, illness category, precision, recall, as well as F1, are presented in the first, fourth, and fifth columns of the Table 3, respectively. The maize leaf image is segmented for precise pixel extraction to retrieve the pixels and image attributes. Figure 3 illustrates the picture segmentation levels procedure. In Table 3, the letters healthy leaves (HL), leaves spot gray (LSG), north leaf blight (NLB), and common leaf rust (CLR). Furthermore, the proposed model exhibits impressive performance metrics for healthy leaf disease, with precision, recall, and F1-score values of 99.7%, 99.94%, and 99.82%, respectively. In the case of detecting grey leaf spots on maize leaves, the EKNN model achieves precision, recall, and F1-score rates of 99.87%, 99.1%, and 99.48%, respectively. Additionally, the EKNN model surpasses the benchmarks with precision at 99.48%, recall at 99.88%, and an F1-score of 99.83% for North leaf blight disease, while maintaining similar excellence with percentages of 99.77%, 99.88%, and 99.83% for common rust disease detection.

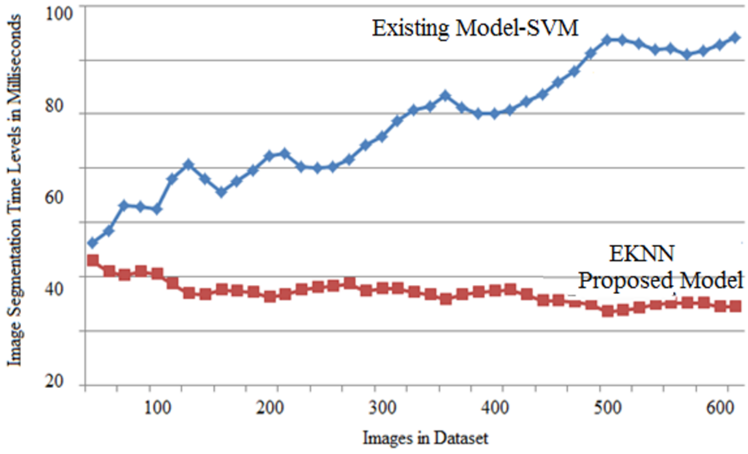

Figure 3. Image segmentation levels

Table 3. Comparison of various existing methodologies with EKNN

Model	Category	Precision	Recall	Fl
Alexnet		HL	95.31	95.31
		LSG	94.39	94.28
		NLB	93.51	94.46
		CLR	92.72	94.87
DMS-Robust Alexnet		HL	99.2	98.44
		LSG	99.16	98.21
		NLB	98.03	98
		CLR	98.95	98.47
EKNN		HL	99.7	99.94
		LSG	99.87	99.1
		NLB	99.48	99.48
		CLR	99.77	99.88

In Figure 4's receiver operating characteristic (ROC) curve for the EKNN model, four different leaf types are depicted: Healthy leaf, grey leaf spot, North leaf blight, and common rust. This ROC graph illustrates the relationship between the true positive (TP) rate and the true negative (TN) rate. Each leaf disease is distinctly differentiated using different colors. Figure 5 provides a comparative evaluation of disease detection between the proposed model and existing models, showcasing that the proposed method exhibits higher accuracy compared to traditional approaches.

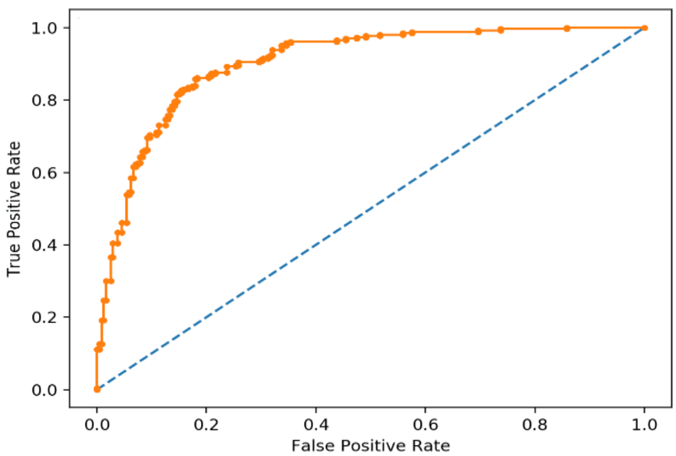

Figure 4. ROC curve

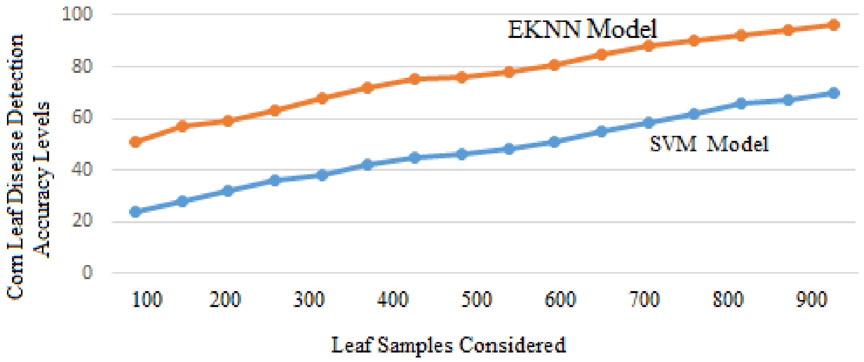

Figure 5. Accuracy levels for disease detection

4. CONCLUSION

Due to the widespread use of the maize crop, early identification of maize leaves is deemed essential. As a result, enhanced KNN is created for the absolute detection of maize illness and further differentiation of disease groups. To produce high-quality features, EKNN also uses advanced mathematical modelling. Here, fine and coaCLRe features are obtained using the suggested approach to enhance classification accuracy. To further attain low dimensionality, limited intensity-DOR is used to optimize the intensity relationships between nearby pixels. Also, an enhnaced mechanism technique called a "Directional Set" is devised for grouping nearby pixels into different sets by pointing in a certain direction. The proposed model EKNN is assessed in light of many established and traditional mechanisms. Furthermore, the proposed model achieves impressive values for accuracy, sensitivity, specificity, and AUC, registering at 99.86%, 99.60%, 99.88%, and 99.75%, respectively. Moreover, a more in-depth comparative analysis is conducted, considering metrics like the F1 score, recall, and precision.

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